Development of Smart Decision Support System using Prescriptive Analytics

Synopsis
Submitted in the partial fulfilment for the requirements of
Doctor of Philosophy
In
Computer Science

Submitted by

Akella Vandana

Under the supervision of

Prof. Preetvanti Singh
Department of Physics and Computer Science
Faculty of science

Department of Physics and Computer Science
Faculty of Science
Dayalbagh Educational Institute (Deemed to be University)
Dayalbagh, Agra-282005

2021

INTRODUCTION

The dynamic, turbulent and volatile modern business environment necessitates demand for the accurate, relevant, complete and timely decision-making process. This decision-making process involves extensive analysis of large data volumes from heterogeneous sources for strategic management which may be imprecise and incomplete. Thus, new analytical tools with efficiency and immense capability are required to deal with this type of data. Business analytics is one such field that allows decision-makers to quantify the effects of making a change to business strategy.

1.1 Business Analytics

Business analytics is the application of computer science, statistics and operations research to compute, evaluate and get the knowledge and understanding of the meaning of data. Figure 1 illustrates the role of business analytics. Business intelligence analyzes what happened and how it happened in the past leading to the present instant. Business analytics, on the other hand, predicts why's of *what will occur in the future*.

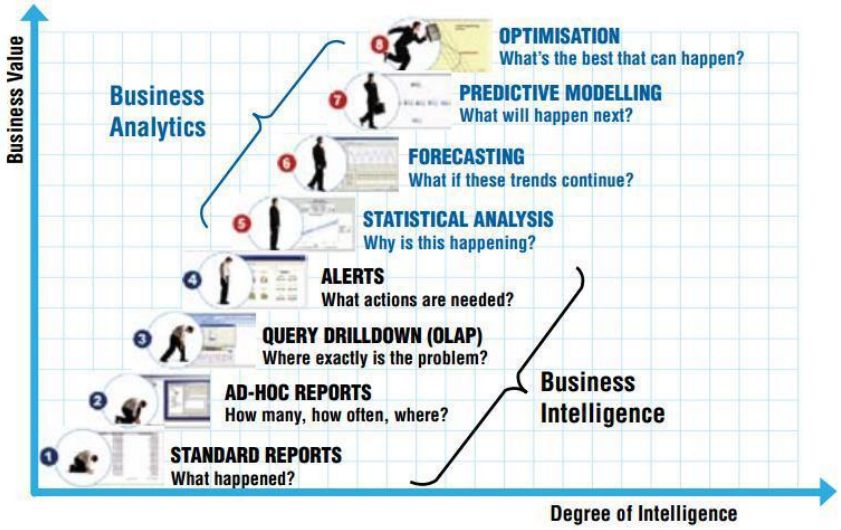

Figure 1: Business Intelligence and Analytics (Varalakshmi, Pavani & Ramadevi, 2019)

Business analytics enables organizations to make quicker, better, and more intelligent decisions for creating business values. It is used by companies that are committed to making data-driven decisions. Business analytics is categorized into four main stages based on difficulty levels, value and intelligence (Figure 2) (Akerkar, 2013; Krumeich, Werth & Loos, 2016; Šikšnys & Pedersen, 2018):

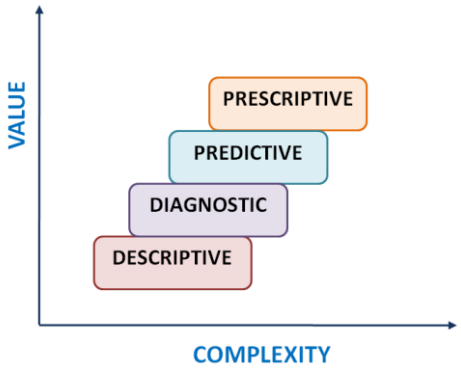

Figure 2: Types of Analytics

- **Descriptive analytics**: This form of analysis interprets historical data to understand efficiently the changes that have occurred. It explains *what happened?* It is a field of statistics that focuses on gathering and summarizing raw data to be easily interpreted. The field is used across a variety of industries.
- **Diagnostic Analytics**: This category of analysis attempts to understand the causes of events and behaviors. It examines *why did it happen*. It is characterized by techniques such as drill-down, data discovery, data mining and correlations.
- **Predictive analytics:** This type of analysis generates future insights based on past data. It applies statistical and machine learning models to the current data for predicting future behavior. It forecasts *what might happen*.
- **Prescriptive analytics**: This kind of analysis emphasizes actionable insights. It attempts to quantify the effect of future decisions to advise on possible outcomes before the decisions are made. The analytics uses the combination of business rules, machine learning and mathematical modeling procedures. It suggests *what should be done*.

1.2 Prescriptive Analytics

Prescriptive analytics, a relatively new field, allows users to prescribe several different possible actions. It predicts not only what will happen, but also why it will happen providing recommendations and suggesting the best possible actions to optimize business practices.

Prescriptive analytics is the most sophisticated type of analytics, at the core of which is optimization. It efficiently organizes the decision-making process for businesses, i.e., it assists in taking actionable steps that are supported by data to solve problems quicker and understand the degree of risk involved.

It is frequently considered as another step towards enhancing data analytics development and driving to optimized decision making ahead of time for performance enhancement.

Prescriptive analytics incorporates the predictive analytics output and utilizes artificial intelligence, optimization algorithms and business rules to provide adaptive, automated, constrained, time-dependent and optimal decisions (Basu, 2013; Hagerty, 2017). Prescriptive analytics has two levels of human intervention: decision support (e.g. providing recommendations) and decision automation (e.g. implementing the prescribed action). The effectiveness of the prescriptions depend upon how well these models incorporate a combination of structured and unstructured data, represent the domain under study and capture impacts of decisions being analyzed (Basu, 2013; Šikšnys & Pedersen, 2018).

Applying prescriptive analytics can help business in recognizing data-driven strategic decisions and assist to avoid the limitations of standard data analytics uses, including:

- Exhausting important resources on lodging data that does not notify business decisions,
- Spending time sifting through unutilized data sets, and
- Missing out on unique revenue streams and insights.

Benefits of prescriptive analytics include

- Generating the roadmap by pulling together data and operations to suggest what to do and how to do it correctly,
- Viewing both real-time and forecasted data simultaneously to make decisions that support sustained growth and success,
- Providing a comprehensive and accurate form of data aggregation and analysis, and
- Creating quality and customized experience for all customers.

Businesses can use this approach to recommend products, deliver timely discounts and provide website recommendations in real-time.

Prescriptive analytics Tools

Various tools to perform prescriptive analytics are (Figure 3):

- **Probabilistic models:** Probabilistic models represent uncertain causal relationships and are used to calculate the likelihood of certain events occurring (Martinez, Cristaldi & Grau, 2009 and Martínez, Cristaldi & Grau, 2013).

- **Machine learning:** Machine learning tools can be used to extract information for finding the best course of action in a given situation (Revathy & Mukesh, 2018 and Srinivas & Ravindran, 2018).
- **Statistical analysis:** Advance statistical techniques can be utilized to predict trends and behavior patterns (Kawas, Squillante, Subramanian & Varshney, 2013).
- **Mathematical programming:** Mathematical programming techniques are utilized to arrive at optimal or near-optimal solutions for complex decision-making problems. The techniques help in planning the best possible allocation of scarce resources (Ghoniem, Ali, Al-Salem, & Khallouli, 2017 and Ito & Fujimaki, 2017).
- **Evolutionary computation:** Evolutionary computation, a family of algorithms by biological evolution, is used for solving complex problems in data-rich environments where exact solutions cannot be derived (Dey, Gupta, Pathak, Kela & Datta, 2019).
- **Simulation:** Simulation is used to improve the effectiveness of decisions, test new ideas about business decisions, mitigate risk about a process or system, and analyze how modifications will affect an existing process or system (Giurgiu et al., 2017 and Jank, Dölle & Schuh, 2018).
- **Logic-based models:** Logic-based models may include rule-based systems, representation of expert knowledge and elicitation of domain knowledge for supporting proactive decision making (Cho, Song, Weber, Jung & Lee, 2015 and Srinivas & Ravindran, 2018).

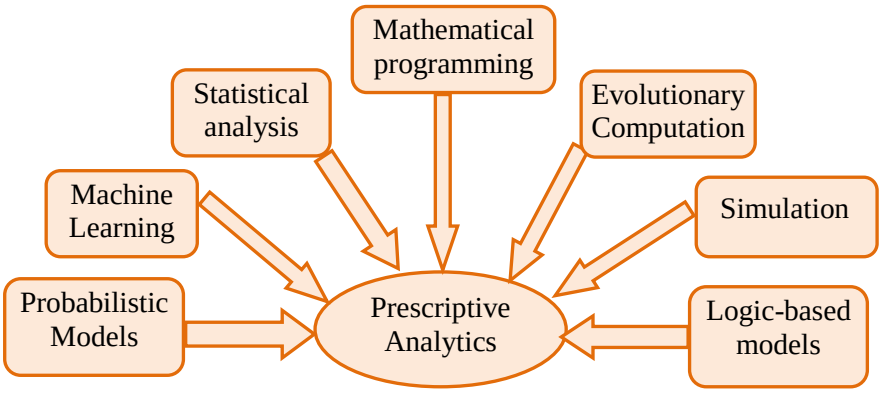

Figure 3: Scope of Prescriptive Analytics

Pillars of prescriptive analytics are:

1. **Hybrid Data**

   Modern business deals with *hybrid data* which is a combination of unstructured and structured data. This empowers businesses to use all the available data to make the best decisions possible.

2. **Integrated Predictions and Prescriptions**

   Prescriptive analytics is about seeing and then shaping the future. The symbiotic integration of predictions and prescriptions is the key to widespread adoption and the inherent value of prescriptive analytics.

3. **Prescriptions**

   Prescriptions, i.e., recommended time-dependent actions to improve the future are generated using several methods. A prevalent method of generating prescriptions is through a guided framework of business rules. A more scientific and rigorous way to produce prescriptions to improve the future is through operations research. To generate the most effective and timely prescriptions both business rules and operations research must be used synergistically.

4. **Adaptive Algorithms**

   As the business process evolves, the prescriptive analysis technology should continually re-predict and re-prescribe so that the prescriptions remain relevant. Due to rapid growth in data volume, velocity and variety, the prescriptive analytics technology must be able to automatically recalibrate all its built-in algorithms and automatically create new algorithms. This recalibration should also be adaptive (dynamic and/or continual) for successfully managing the business process. Another important factor is the *action-ability* of the prescriptions which may be different for different business processes.

5. **Feedback Mechanism**

   To know if the generated prescriptions are acting correctly, prescriptions automation is required. Prescription automation is elaborating and controlling a built-in process to automatically action the prescriptions.

Prescriptive analytics is a critical advancement in analytics. Currently, prescriptive analytics appears to have attracted attention in the following domains:

- *Business:* ease the work of business people by taking appropriate decisions regarding a product (Ghosh, Gupta, Chattopadhyay, Banerjee & Dasgupta, 2016 and Wang, Cheng & Deng, 2018).
- *Finance:* helps investors in purchasing and cost estimation (Baur, Klein & Steinhardt, 2014; Aref et al., 2015; and Bertsimas & Kallus, 2019).
- *Sports*: help to make crucial decisions for analyzing the game (Ghoniem, Ali, Al-Salem & Khallouli, 2017).
- *Risk Assessment:* reduces operational cost, increases operational efficiency, business process optimization (Groenhof et al., 2019 and Sutton et al., 2020).
- *Academics:* recommends an adjustment to the student's learning path (Soriano, Capucao & Palaoag, 2018 and Melnikov, Ryzhkova, Ivukina & Barkov, 2019).
- *Agriculture:* prescribes a method to improve crop performance (Laude, 2018).
- *Capacity planning:* prescribes capacity management and planning decisions directly from historical demands for various services (Notz & Pibernik, 2019).
- *Medical:* helps doctors to understand the disease by developing a medical decision support system (Siu, Tang, Choy, Lam & Ho, 2019 and Iadanza et al., 2020).

1.3 Decision Support Systems (DSS)

Decision Support Systems (DSSs) are interactive computerized systems that support business and organizational decision-making activities, making it possible to compile useful information from raw data, documents, personal knowledge and business models. It improves the operational efficiency of a business by enabling decision-makers to make smart decisions.

Decisions may be structured, unstructured or semi-structured. The type of the decision can be evaluated in terms of its key components: (a) The data collected by a decision-maker to be used in decision making, (b) The process selected by the decision-maker to combine this data, and (c) The evaluation or learning component that compares decisions and examines them to see if there is a need to change either the data being used or the process that combines the data. Structured decisions are the decisions in which all three components of a decision, the data, process and evaluation, can be

determined. Unstructured decisions are made in instances in which all elements of the business environment are not completely understood. Semi-structured decisions are characterized as having some agreement on the data, process and evaluation to be used, and are also typified by efforts to retain some level of human judgment in the decision-making process. The focus of DSS is mainly a semi-structured decision.

Key DSS Functions

Functions of DSS include

- *Information management:* refers to the storage, retrieval and reporting of information in a structured format convenient to the user.
- *Data quantification:* is the process by which large amounts of information are condensed and analytically manipulated into a few core indicators that extract the essence of data.
- *Model manipulation:* refers to the construction and resolution of various scenarios to answer *what-if* questions. It includes the processes of model formulation, alternatives generation and solution of the proposed models.

Fundamental components of a DSS

The three main components of a decision support system to accomplish the above tasks include:

1. **The Database system**: It contains data from various internal sources and external sources. This may be a small database or a standalone system or a huge data warehouse supporting the information needs of an organization.
2. **The Model base System**: It consists of various mathematical and analytical models that are used to analyze the complex data. A decision support system may compromise different models where each model performs a specific function depending upon users' requirements.
3. **The User Interface**: It is an interactive graphical interface that makes the interaction easier between the DSS and its users. It displays the results (output) of the analysis in various forms, such as text, table, charts or graphics. Users can select the appropriate option to view the output according to their requirements.

DSS Limitations

While decision support systems are gaining popularity in various fields, these have some limitations:

- **Level of User-Friendliness:** This remains an issue particularly for small business operations that do not have significant resources in terms of technological knowledge.
- **Hard-to-Quantify Factors:** The what-if analysis enables decision-makers to study the outcome of mathematical relationships of variables and their impact on different variables. Still there are factors like future interest rates, risks and new legislations that are hard to quantify but are important to be considered for decision making.
- **Processing Model Limitations:** Another limitation is that the decision-maker may not be fully aware of the limitations or assumptions of the particular processing model. There may be instances in which the decision-maker has an idea of the knowledge that is desired, but not necessarily the best way to get that knowledge.

Prescriptive analysis based decision support will enable the decision-maker and the analyst to produce more accurate predictions and suggest well-defined decision options for taking advantage of prospects or alleviating future risks.

LITERATURE REVIEW

Currently, the majority of business analytics efforts are spent on descriptive analytics and predictive analytics. However, prescriptive analytics, which discovers an excellent course of action for the future, is not being explored much (den Hertog & Postek, 2016; Soltanpoor & Sellis, 2016; Habeeb et al., 2019). However, due to complexities in data and the need for optimized solutions, prescriptive analytics is progressively gathering the research interest. Concepts of prescriptive analytics are discussed in Devriendt, Moldovan & Verbeke (2018); Frazzetto, Nielsen, Pedersen & Šikšnys (2019); and Ansari, Glawar & Sihn (2020).

Prescriptive Analytics: Methods and Approaches

Seeing the importance of prescriptive analytics, Song et al. (2014) implemented a prescriptive analytics system for improving research performance based on 5W1H questions to build actionable strategies. Brodsky et al. (2015) proposed an architectural design and software framework for fast development of the analytics solutions for dynamic production processes to support the storage of

modular, extensible and reusable knowledge base of process performance models. Du, Plaisant, Spring & Shneiderman (2016) focused on the presentation and explanation of recommendations of temporal event sequences using a prescriptive analytics interface. Hupfeld, Maccioni, Sesemann & Ravazzolo (2016) demonstrated how advanced analytics can be integrated and adapted to improve business management. Poornima & Pushpalatha (2016) addressed the concept of big data and various types of analytics that can be considered by the researchers for further analysis.

Bedeley, Ghoshal, Iyer & Bhadury (2018) illustrated the uses of business analytics tools by presenting a mapping of business analytics capabilities for a firm from a value chain perspective. Ceselli et al. (2018) proposed a methodology to integrate arbitrary time-period aggregation methods into a network optimization framework by applying simple consecutive period aggregation and agglomerative hierarchical clustering. Ramannavar & Sidnal (2018) proposed a distributed architecture that integrates advanced analytics for mapping a job to resumes utilizing semantic technologies. Ceselli, Fiore, Premoli & Secci (2019) proposed a general data-driven framework including an optimization core that includes an exact algorithm for a variant of the generalized assignment problem. Huang, Bergman and Gopal, (2019) addressed the problem of selecting expansion locations for retailers selling add-on products, demand of which depends on the demand of another base product.

The methodology of prescriptive analytics is based on data science (Tranfield, Denyer & Smart, 2003). Linear programming and its extensions are the most used optimization methods in prescriptive analytics. It was used for planning sales force assignments based on predictions about the sales impact by Von Bischhoffshausen, Paatsch, Reuter, Satzger & Fromm (2015) and for finding a feasible combination of environmental alternatives that minimize the emissions of transport fleets by Wu & Yang (2017). Binary linear programming was utilized by Lo & Pachamanova (2015) for recommending products or services to customers by formulating the problem as a multiple treatment optimization models with binary decision variables. Linear integer programming is used for redesigning the enterprise software to support mathematical optimization by Aref et al. (2015) and for capacity planning in stadiums for sports events by Ghoniem, Ali, Al-Salem & Khallouli (2017).

Ito & Fujimaki (2017) proposed a prescriptive analytics model based on binary quadratic non-linear programming for deriving the optimal price strategy based on a customer-centric pricing approach.

Stochastic optimization technique was applied by Berk, Bertsimas, Weinstein & Yan (2019) and Bertsimas & Kallus (2019) to focus on decision making under uncertainty. Ho & Hanasusanto (2019) considered generic stochastic optimization problems in the presence of side information which enables a more insightful decision. Caro & Martínez-de-Albéniz (2020) developed a simple model to study the dynamics of building up a follower base and then combined the model with stochastic dynamic programming to optimize the content provider's profit. Adaptive robust optimization was utilized by Bertsimas & Van Parys (2017) to solve an analytics problem where the characterization of the uncertainty sets can be data-driven. Berk, Bertsimas, Weinstein & Yan (2019) examined human resource planning decisions made at firms that sell contract-based consulting projects using concepts from robust optimization to dynamically make hiring decisions that maximize profit while remaining flexible also. Bayesian optimization method, which first evaluates a small number of randomly selected function values, and then fits a Gaussian process regression model, was applied by Gardner, Kusner, Xu, Weinberger & Cunningham (2014), Harikumar et al. (2018a, b) and Letham, Karrer, Ottoni & Bakshy (2019).

Evolutionary computation methods can be used for providing approximate solutions efficiently. The genetic algorithm was studied as a prescriptive analytics tool by Dey, Gupta, Pathak, Kela & Datta (2019). Giurgiu et al. (2017) applied simulation over the random forest model for prescribing improved actions to servers by using the information available from the incident tickets. The stochastic simulation was explored by Jank, Dölle & Schuh (2018) to maximize the benefits of a company's product portfolio following the corporate objectives.

Machine Learning algorithms have also been used in predictive analytics. Revathy & Mukesh (2018) addressed the approach of data placement using advanced machine learning techniques to realize a more secure data/infrastructure. Srinivas & Ravindran (2018) developed a prescriptive analytics framework using machine learning algorithms to improve patient satisfaction and resource utilization.

The above-discussed methods for prescriptive analytics can be integrated to provide more efficient decisions. Jiang, Jensen, Cao and Kumar (2010) combined mathematical programming and probabilistic models to build business intelligence applications having predictive and prescriptive analytics capabilities. Kawas, Squillante, Subramanian & Varshney (2013) used multiple linear

regressions and mixed-integer linear programming to maximize business revenue and profit. Shroff et al. (2014) proposed a framework based upon reinforcement integrated with simulation and optimization in an online learning scenario. Ghosh, Gupta, Chattopadhyay, Banerjee and Dasgupta (2016) combined methods from the mathematical programming, machine learning and logic-based models to define, monitor, rank and classify a set of key performance indicators measuring the operational efficiency of the business process. Appelbaum, Kogan, Vasarhelyi & Yan (2017) proposed a managerial accounting data analytics framework based on the balanced scorecard theory using univariate and multivariate regression analysis and big data analytics. Kopcso & Pachamanova (2017) developed a method to integrate predictive and prescriptive analysis by using a decision tree, taking a case study of customer service to create recommendations for business stakeholders. Thammaboosadee and Wongpitak (2018) combined evolutionary computation and k- means clustering to allocate electrical equipment's parts taking into consideration the customer behavior and the company policy. Wang, Cheng and Deng (2018) proposed a stochastic simulation method over a Bayesian Belief Network to conduct fact-based decision making based on key performance indicators in a data-driven way.

Prescriptive Analytics: Application areas

This type of advanced analytics has been applied to different areas. Souza (2014) described the application of advanced analytics techniques to supply chain management by categorizing the applications in terms of descriptive, predictive, and prescriptive analytics and along with the supply chain operations reference model. Cho, Song, Weber, Jung & Lee (2015) introduced a journal recommendation model to prescribe strategies for enhancing research performance from the InSciTe system by considering their research subjects and capabilities. Adra et al. (2016) discussed the reusability and extensibility of simulation models and their roles in predictive and prescriptive analytics using real-time data connectivity.

Achenbach & Spinler (2018) provided arrival time prediction combined with a cost index optimization model for short-haul flights. Ayhan, Costas & Samet (2018) proposed a prescriptive analytics system to address a long-range aircraft conflict detection and resolution problem. The system resolves the aircraft conflict by prescribing an alternative solution that is optimized by perturbing at least one of the

trajectories involved in the conflict. Event Action, a prescriptive analytics tool, was used by Du, Malik, Koh & Theocharous (2018) in a digital marketing scenario. Kaur & Mann (2018) proposed a generic architecture for enabling AI-based healthcare analytics platforms by using open source technologies. The system will be able to extract useful knowledge that helps in real-time decision making and medical monitoring. Srinivas & Ravindran (2018) developed a prescriptive analytics framework to improve the performance of an appointment system concerning patient satisfaction and resource utilization.

Fang, Gao & Hu (2019) developed a prescriptive analytics method for improving the cost-effectiveness in clinical decision making, a critical health care dimension that can be benefited from such analytics. Gharib Shirangi et al. (2019) presented a comprehensive prescriptive analytics framework for completion optimization in unconventional resources. The AutoML process automatically searches among various machine-learning algorithms, to find the best algorithm and the best-associated hyper-parameters. Vakhutinsky, Mihic & Wu (2019) introduced a prescriptive analytics approach to solving markdown-pricing optimization for an e-commerce retailer capable of price differentiation based on customer demand elasticity and the cost of delivery or other services. Vater, Harscheidt & Knoll (2019) provided a review of key elements for prescriptive analytics in manufacturing and highlighted requirements for prescriptive analytics based production control. Notz & Wolf (2020) proposed data-driven approaches to solve a specific class of capacity sizing problems with uncertainty, time-varying arrival rates and patients that do not abandon the queue while waiting for service. Venkatachalam, Acharya, Oba & Nakayama (2020) described an implementation of a swapper optimization suite for the airlines in Japan that uses optimization models to generate the optimal swaps as decision solutions.

Decision Support System

A DSS is a computerized system that supports the business and organizational decision-making processes. Concepts of DSS can be understood from Power & Sharda (2007); Musen, Middleton & Greenes (2014); Bezemer et al. (2019); Groenhof et al. (2019); Martensen et al. (2019); Walsh et al. (2019) and Sutton et al. (2020).

DSS: Methods and Approaches

Fekri-Ershad, Tajalizadeh and Jafari (2013) developed a DSS for universities by combining artificial intelligence methods. Khademolqorani & Hamadani (2013) integrated the DSS with data mining and multi-criteria decision-making methods. Guo, Ngai, Yang & Liang (2015) proposed radio frequency identification based intelligent DSS architecture for production monitoring and scheduling in a distributed manufacturing environment. Sabou, Brașoveanu & Önder (2015) described a linked data-based solution to build an integrated dataset as a basis for a DSS capable of enabling cross-domain decision-making. Giuseppe et al. (2016) presented a DSS for real-time decision making on discount and promotion actions. The system makes decisions based on recognition and assessment of situations of interest for the consumers, modeled with heuristics related to behavioral economics results. Antonio, de Almeida & Nunes (2019) implemented a DSS for predicting hotel booking cancellations and studied its impact on demand-management decisions based on an automated machine learning system designed to learn continuously. Ayodeji & Liu (2019) presented a technique to develop a fault diagnostic decision support using recurrent neural network and principal component analysis. Dellermann, Lipusch, Ebel & Leimeister (2019) developed design principles for a Hybrid Intelligence DSS that combines the complementary capabilities of human and machine intelligence. Fiarni, Sipayung & Tumundo (2019) designed and developed an academic DSS by adopting the theory of reasoned action concept and data mining as a factor analytic approach to extract rules for its knowledge model. García-Alonso et al., (2019) introduced a DSS to improve knowledge on the health ecosystem and resource allocation by integrating the Monte-Carlo simulation engine, a fuzzy inference engine prototype and basic statistics as well as system stability and entropy indicators. Hayashi, Wakabayashi, Kurniawan, Shimojyo & Kida (2019) proposed DSS for juries in court by investigating the factor of the social presence of a robot by using an actual robot and comparing it with a computer graphics robot. Kurniawan, Kridalaksana & Jundillah (2019) proposed a DSS for selection of soang superior brood using the weighted product and simple additive weighting methods for determining the calculation accuracy of the decision-making process. Melnikov, Ryzhkova, Ivukina & Barkov (2019) presented a pedagogic DSS for organizational monitoring and evaluation of the educational process. Hydrological and water management resource models have been combined with the DSS by Ruiz-Ortiz, García-López, Solera

& Paredes (2019) for a better design of the basin management rules taking an Andalusian basin of the Atlantic zone (Spain) as the case study. Siu, Tang, Choy, Lam & Ho (2019) developed an intelligent clinical DSS for care managers to improve assessing the long-term care needs of the elderly using artificial intelligence techniques. Tang et al. (2019) described an adaptive DSS to enable decision making in formulating nursing care strategies by integrating cloud computing technology and the case-based reasoning technique.

DSS Applications

Applications of DSS can be found in solving many real-life problems. Navarro-Hellín, Martínez-del-Rincon, Domingo-Miguel, Soto-Valles & Torres-Sánchez (2016) developed a Smart Irrigation DSS to manage irrigation in agriculture. The system estimates the weekly irrigation needs of a plantation, based on both soil measurements and climatic variables. Rashidi, Ghodrat, Samali, Kendall & Zhang (2017) developed a DSS for asset management of steel bridges within acceptable limits of safety, functionality and sustainability.

Vinnik & Scholl (2005) proposed a DSS for the university's capacity planning to optimize the academic decision making by allowing simulation and evaluation of strategic plans. Abu-Naser, Almasri, Abu Sultan & Zaqout (2011) proposed a DSS based on mining knowledge from large amounts of data generated from the operating institution to its business. Vohra & Das (2011) proposed a DSS for developing student admission policies in a higher education institute. Fakeeh (2015) presented a DSS taking in the present systems and databases of some institute for decision making in diverse explicit circumstances or settings. Soriano, Capucao & Palaoag (2018) developed a decision support model for managing college academic workload in State Universities and Colleges using a feed-forward ANN trained by a back-propagation algorithm.

Horner, Rautenbach, Mbananga, Mashamba & Kwinda (2013) investigated the utility of e-health DSSs with compliance of maternity care guidelines by health workers in South Africa. Dios, Molina-Pariente, Fernandez-Viagas, Andrade-Pineda & Framinan (2015) embedded optimization procedures to support decisions for assigning the operating rooms and dates of patients in a waiting list by implementing a DSS. Moja et al. (2016) implemented an evidence based DSS to evaluate the effectiveness of clinical practice and the quality of care of a multi-specialty hospital. Kilsdonk, Peute

& Jaspers (2017) provided an integrated and differentiated understanding of factors influencing guideline-based CDSS implementation and illustrated the gaps in the current literature. Benditz et al. (2019) investigated the concordance of a DSS and the recommendation of spinal surgeons regarding back pain. Debeljak et al. (2019) designed a DSS for soil navigator by utilizing a qualitative approach based on multi-criteria decision modeling. Iadanza et al. (2020) presented a clinical DSS using Machine Learning Chromatic Pupillometry for supporting inherited diseases diagnosis in pediatric subjects. Sutton et al. (2020) provided an overview of using clinical DSS and concluded with evidence-based recommendations for minimizing risk in CDSS design and implementation

Dotoli, Hammadi, Jeribi, Russo & Zgaya (2013) presented a DSS for co-modal transportation that answers multiple route planning requests in a co-modal setting with vehicle preference and conflicting criteria, e.g., costs, time, and gas emissions minimization. Yoo, Goo, Huang, Nam & Woo (2017) investigated the impact of the important smart tourism technology characteristics on travel decision support satisfaction and the moderating effects of self-efficacy on the main relationships. Savvopoulos et al. (2019) presented a tourism DSS based on the destination datasets to offer recommendations towards enhancing the innovation capacity.

DSS in Prescriptive Analysis

Song et al. (2013) and Lee, Cho, Gim, Jeong & Jung (2014) introduced a prescriptive analytics system, InSciTe advisory, to provide researchers with advice on their future research direction and strategy. A DSS using linear integer programming was developed by Baur, Klein & Steinhardt (2014) for optimally determining hotel room prices to be published in the tour operator's brochure. Gröger, Schwarz & Mitschang (2014) prescriptively generated action recommendations during process execution to avoid a predicted metric deviation. Chalmers, Hill, Zhao & Lou (2015) investigated using prescriptive analytics to recommend optimal in-brace corrections for braced adolescent idiopathic scoliosis patients. Von Bischhoffshausen, Paatsch, Reuter, Satzger & Fromm (2015) developed a DSS for assigning sales rep to customer accounts by utilizing predictive and prescriptive analytics. Pospieszny (2017) proposed various use cases for prescriptive analytics to enhance software estimation, optimize resource utilization, and improve product quality for increasing the possibility of successful project completion. Boulila, Farah & Hussain (2018) developed a tool for analyzing remote

sensing big data by gathering knowledge for decision support in remote sensing fields. Stein, Meller & Flath (2018) illustrated the main steps and major challenges in developing and instantiating a predictive decision support system. By establishing a scalable and generic feature generation approach as well as leveraging techniques from statistical learning, and were able to improve the forecasts of the leak position by approximately 90%.

The motivation of proposed work

From the above discussion, the following are the main motivational observations:

- *Prescriptive analytics is the most sophisticated type of business analytics and can bring the greatest intelligence and value to businesses (Šikšnys & Pedersen, 2018). Compared to descriptive and predictive analyses, prescriptive analytics is still less mature (Hagerty, 2017).*

  Modern business constantly seeks ways to improve efficiencies, reduce waste and optimize resources as part of their ongoing business practices. To increase data analytics maturity and to optimize decision making ahead of time it is required to develop predictive analysis tools.

- *For prescriptive analytics technology to be transformative, it must be able to process hybrid data (Basu, 2013).*

  To process hybrid data, there is a need to combine new technologies with traditional prescriptive analysis tools. These traditional disciplines such as applied statistics, operations research remain invaluable, but these are not designed to process the image, video, audio and text.

- *Many decision situations faced by executives in small business are one-of-a-kind, and one-shot occurrences requiring specifically tailored solution approaches. This unstructured or semi-structured nature of decision situations aggravates the problem of limited resources and staff expertise available to a small business executive to analyze important decisions appropriately (Encyclopedia, DSS, 2019).*

  Hence, a decision-making model must be developed for better and improved decision support to provide executives with assistance in business guidance and management.

- *The prescriptive analysis aims at prescribing the best decision options to take advantage of the predicted future utilizing large amounts of data (Šikšnys & Pedersen, 2018).*

This requires incorporating intelligent recommendations within the decision support system to provide adaptive, automated, and optimal decisions.

PROPOSED WORK

The main goal of this research study is to develop a smart recommendation based decision support system using prescriptive analytics for business performance improvement.

Objectives of the proposed study

1. To develop an optimization based prescriptive analytics tool for the defined application area,
2. To combine new technologies with the developed traditional prescriptive analytics tool for the selected area,
3. With the help of the developed prescriptive analytics tool, design and develop a decision support system for providing smart recommendations for the chosen problem statement, and
4. To provide a real-life implementation of the developed system.

Methodology to achieve the objectives

The major tasks of the systems are defined as follows.

- To achieve the 1st objective, an optimization-based module will be developed by integrating the prescriptive analytics methods like machine learning techniques with mathematical programming techniques.

  This study will deal with the data based on the application area chosen for the study area. The data set for the study will comprise of structured data (preferably SQL database) and unstructured data (preferably No-SQL databases)
- For attaining the 2nd objective, natural language processing or image processing will be integrated with traditional disciplines (operations research, or applied statistics) to deal with hybrid data.
- The 3rd objective of the study will be accomplished by adding the knowledge base and the model base components, comprising of the above developed intelligent tools to provide smart recommendations. The variables and parameters for DSS will be selected as per the study area.

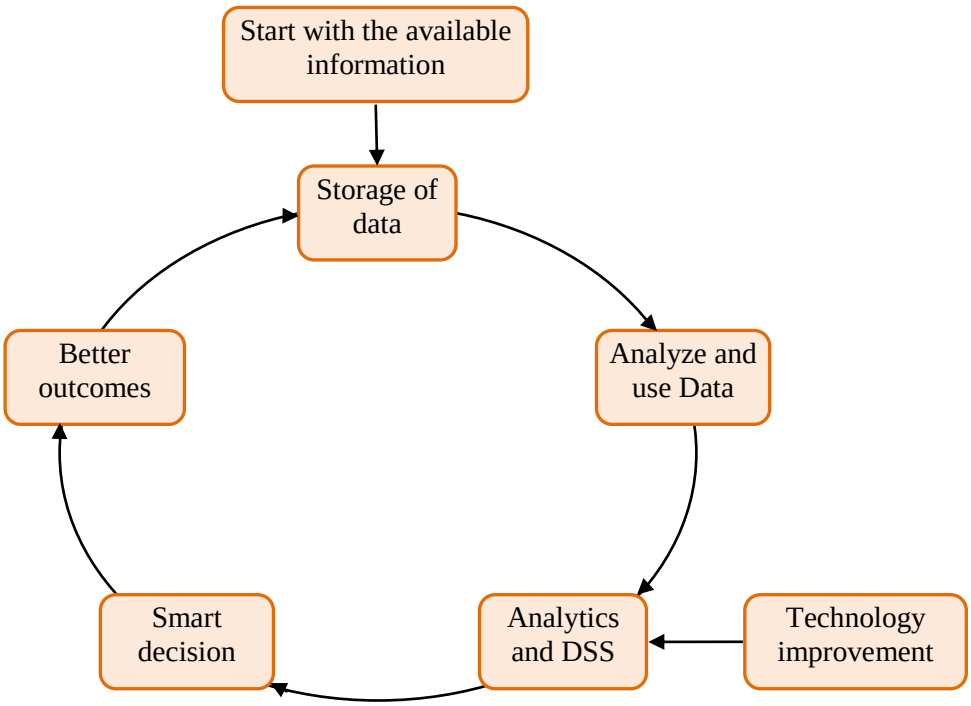

Figure 4: Process to achieve the objectives

- The developed system will be implemented for resource optimization or business process optimization in healthcare or academics (taking Dayalbagh Educational Institute as a case study).

Steps in constructing the proposed system

The proposed system will be designed and developed using the following steps:

1. **Problem Identification:** In this stage the problems will be specified, DSS objectives and the decisions to be supported will be identified. The main work in this stage will include:
   a) Understanding the nature of the problem
   b) Understanding the number of possible solutions
   c) Evaluating and select a suitable option
2. **Requirement Analysis:** In this stage the functional and nonfunctional requirements will be identified and the outputs that must be given by the framework will be decided. The main work in this stage will be:
   a) Understand the requirements.
   b) Analyze the scope and extent.

c) Analyze the number of resources required.

d) Analyze the process to be followed

3. **Design**: Once the problem and requirements are identified, the solution for the proposed system based on the requirements and the limitations recognized in the previous stage will be defined. The important activities performed in this stage are:

   a) Design of the technical architecture.

   b) Design of system models.

   c) Design the main components of the framework.

4. **Development:** In this phase the system will be developed to solve the defined problem. The development of the system will support the decision-making process required for resolving that problem. Prototyping is an efficient method that can be used for successful system development.

5. **Testing:** The system will be validated through the testing phase. The system undergoes the process of unit, integration and other types of testing based on the requirement for various problems or issues and revision of the framework takes place.

6. **Final implementation:** This is the final stage. The full-scale system developed is implemented in the area of health care or education, depending upon the availability of the appropriate data and resources.

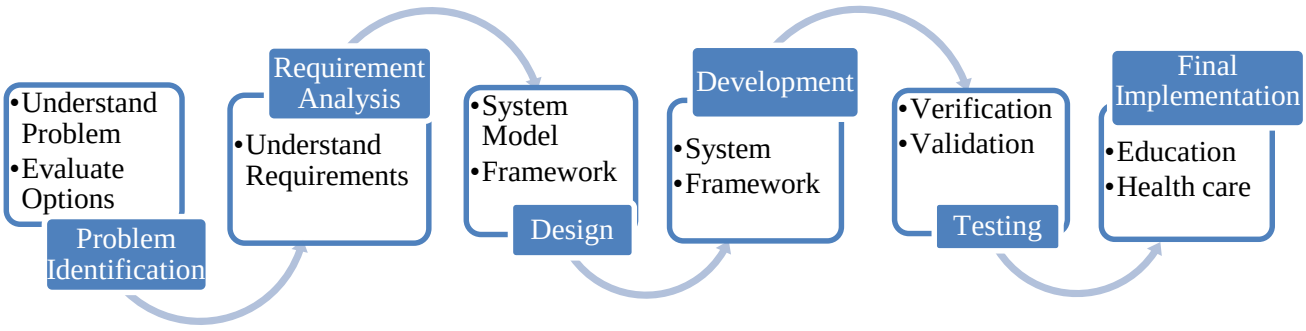

Figure 5: Steps in constructing the proposed system

The determined analytics solutions will aim to provide better decision support to the decision-makers of the proposed system so that they can make better decisions augmented by relevant information. The decision support capabilities of the proposed system will be divided into the following five categories, enabling to answer different types of questions:

- Planning analytics: What is the plan?
- Descriptive analytics: What happened?
- Diagnostic analytics: Why did it happen?
- Predictive analytics: What will happen next?
- Prescriptive analytics: What should be done about it?

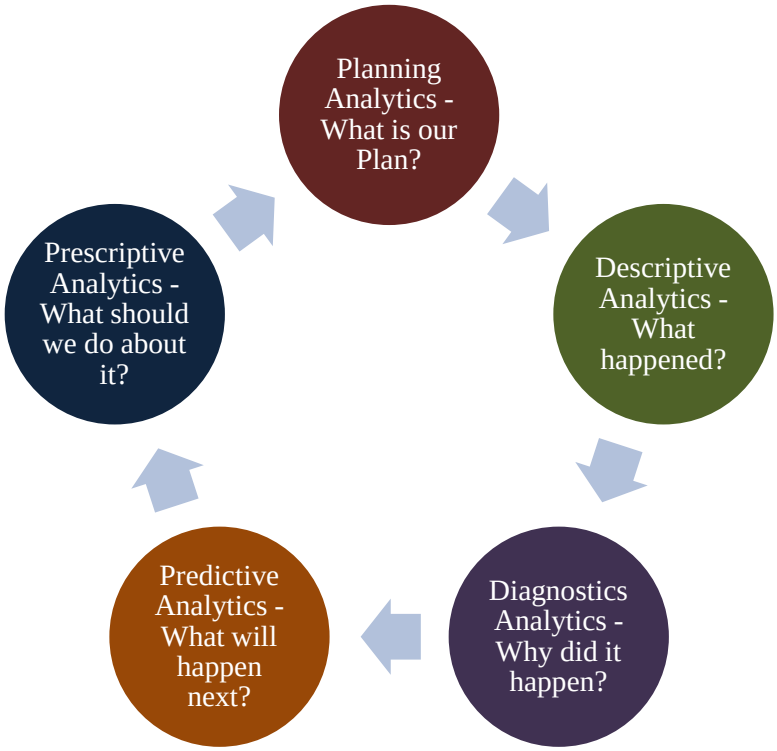
Planning Analytics - What is our Plan?
Descriptive Analytics - What happened?
Diagnostics Analytics - Why did it happen?
Predictive Analytics - What will happen next?
Prescriptive Analytics - What should we do about it?

Figure 6: Categories of decision support capabilities of the proposed system

Prescriptive analytics is relatively complex to administer and is not yet used in the daily course of business. If implemented correctly, these can have a large impact on how businesses make decisions. The proposed system will enable business people to make sure they are delivering the right products at the right time, and optimizing the customer experience.

References

Abu-Naser, S. S., Almasri, A., Abu Sultan, Y. S., & Zaqout, I. S. (2011). A prototype decision support system for optimizing the effectiveness of elearning in educational institutions.

Achenbach, A., &Spinler, S. (2018). Prescriptive analytics in airline operations: Arrival time prediction and cost index optimization for short-haul flights. *Operations Research Perspectives*, *5*, 265-279.

Adra, H., Roeder, T. M. K., Frazier, P. I., Szechtman, R., Zhou, E., &Huschka, T. (2016). Realtime predictive and prescriptive analytics with real-time data and simulation. In *Proceedings of the 2016 Winter Simulation Conference* (pp. 3646-3651). Institute of Electrical and Electronics Engineers, Inc.

Akerkar, R. (2013). Advanced data analytics for business. Big data computing, 377(9).

Ansari, F., Glawar, R., &Sihn, W. (2020). Prescriptive Maintenance of CPPS by Integrating Multimodal Data with Dynamic Bayesian Networks. In *Machine Learning for Cyber Physical Systems* (pp. 1-8). Springer Vieweg, Berlin, Heidelberg.

Antonio, N., de Almeida, A., & Nunes, L. (2019). An automated machine learning-based decision support system to predict hotel booking cancellations. *An automated machine learning-based decision support system to predict hotel booking cancellations*, (1), 1-20.

Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems*, *25*, 29-44.

Aref, M., ten Cate, B., Green, T. J., Kimelfeld, B., Olteanu, D., Pasalic, E., ... & Washburn, G. (2015, May). Design and implementation of the LogicBlox system. In Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data (pp. 1371-1382).

Ayhan, S., Costas, P., &Samet, H. (2018, November). Prescriptive analytics system for long-range aircraft conflict detection and resolution. In *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* (pp. 239-248).

Ayodeji, A., & Liu, Y. K. (2019). Recurrent neural network-based decision support system. *arXiv preprint arXiv:1910.02219*.

Basu, A. (2013). Five pillars of prescriptive analytics success. *Analytics magazine*, 8-12.

Baur, A., Klein, R., & Steinhardt, C. (2014). Model-based decision support for optimal brochure pricing: applying advanced analytics in the tour operating industry. OR Spectrum, 36(3), 557-584.

Bedeley, R. T., Ghoshal, T., Iyer, L. S., &Bhadury, J. (2018). Business analytics and organizational value chains: a relational mapping. *Journal of computer information systems*, *58*(2), 151-161.

Benditz, A., Faber, F., Wenk, G., Fuchs, T., Salak, N., Grifka, J., ... & Jansen, P. (2019). The Role of a Decision Support System in Back Pain Diagnoses: A Pilot Study. *BioMed research international*, *2019*.

Berk, L., Bertsimas, D., Weinstein, A. M., & Yan, J. (2019). Prescriptive analytics for human resource planning in the professional services industry. *European Journal of Operational Research*, *272*(2), 636-641.

Bertsimas, D., & Kallus, N. (2019). From predictive to prescriptive analytics. Management of Science.

Bertsimas, D., & Van Parys, B. (2017). Bootstrap robust prescriptive analytics. arXiv preprint arXiv:1711.09974.

Bezemer, T., De Groot, M. C., Blasse, E., Ten Berg, M. J., Kappen, T. H., Bredenoord, A. L., ... &Haitjema, S. (2019). A human (e) factor in clinical decision support systems. *Journal of medical Internet research*, *21*(3), e11732.

Boulila, W., Farah, I. R., & Hussain, A. (2018). A novel decision support system for the interpretation of remote sensing big data. *Earth Science Informatics*, *11*(1), 31-45.

Brodsky, A., Shao, G., Krishnamoorthy, M., Narayanan, A., Menascé, D., & Ak, R. (2015, October). Analysis and optimization in smart manufacturing based on a reusable knowledge base for process performance models. In *2015 IEEE International Conference on Big Data (Big Data)* (pp. 1418-1427).

Caro, F., & Martínez-de-Albéniz, V. (2020). Managing Online Content to Build a Follower Base: Model and Applications. *INFORMS Journal on Optimization*, *2*(1), 57-77.

Ceselli, A., Fiore, M., Furno, A., Premoli, M., Secci, S., &Stanica, R. (2018, May). Prescriptive Analytics for MEC Orchestration. In *2018* IEEE. *IFIP Networking Conference (IFIP Networking) and Workshops* (pp. 1-9).

Ceselli, A., Fiore, M., Premoli, M., &Secci, S. (2019). Optimized assignment patterns in Mobile Edge Cloud networks. *Computers & Operations Research*, *106*, 246-259.

Chalmers, E., Hill, D., Zhao, V., & Lou, E. (2015). Prescriptive analytics applied to brace treatment for AIS: a pilot demonstration. *Scoliosis*, *10*(2), S13.

Cho, M., Song, S. K., Weber, J., Jung, H., & Lee, M. (2015). Prescriptive analytics for planning a research-performance strategy. In *Computer Science and its Applications* (pp. 1123-1129). Springer, Berlin, Heidelberg.

Debeljak, M., Trajanov, A., Kuzmanovski, V., Schröder, J., Sandén, T., Spiegel, H., ... & Creamer, R. E. (2019). A field-scale decision support system for the assessment and management of soil functions. *Frontiers in Environmental Science*, *7*, 115.

Dellermann, D., Lipusch, N., Ebel, P., &Leimeister, J. M. (2019). Design principles for a hybrid intelligence decision support system for business model validation. Electronic markets, 29(3), 423-441.

den Hertog, D., &Postek, K. (2016). Bridging the gap between predictive and prescriptive analytics-new optimization methodology needed. Technical report, Tilburg University, Netherlands, 2016. Available at: http://www. optimization-online. org/DB_HTML/2016/12/5779. html.

Devriendt, F., Moldovan, D., & Verbeke, W. (2018). A literature survey and experimental evaluation of the state-of-the-art in uplift modeling: A stepping stone toward the development of prescriptive analytics. *Big data*, *6*(1), 13-41.

Dey, S., Gupta, N., Pathak, S., Kela, D. H., & Datta, S. (2019). Data-Driven Design Optimization for Industrial Products. In Optimization in Industry (pp. 253-267). Springer, Cham.

Dios, M., Molina-Pariente, J. M., Fernandez-Viagas, V., Andrade-Pineda, J. L., &Framinan, J. M. (2015). A decision support system for operating room scheduling. Computers & Industrial Engineering, 88, 430-443.

Dotoli, M., Hammadi, S., Jeribi, K., Russo, C., &Zgaya, H. (2013, December). A multi-agent decision support system for optimization of co-modal transportation route planning services. In the 52nd IEEE Conference on Decision and Control (pp. 911-916).

Du, F., Malik, S., Koh, E., &Theocharous, G. (2018, April). Interactive campaign planning for marketing analysts. In Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems (pp. 1-6).

Du, F., Plaisant, C., Spring, N., &Shneiderman, B. (2016, October). EventAction: Visual analytics for temporal event sequence recommendation. In 2016 IEEE Conference on Visual Analytics Science and Technology (VAST) (pp. 61-70).

Encyclopedia, DSS, available at https://www.inc.com/encyclopedia/decision-support-systems.html

Fakeeh, K. A. (2015). Decision support systems (DSS) in the higher education system. International Journal of Applied Information System (IJAIS), 9(2).

Fang, X., Gao, Y., & Hu, P. J. (2019). A Prescriptive Analytics Method for Cost Reduction in Clinical Decision Making. *MIS Quarterly, Forthcoming*.

Fekri-Ershad, S., Tajalizadeh, H., & Jafari, S. (2013). Design and Development of an Expert System to Help Head of University Departments. arXiv preprint arXiv:1308.0356.

Fiarni, C., Sipayung, E. M., &Tumundo, P. B. (2019). Academic Decision Support System for Choosing Information Systems Sub Majors Programs using Decision Tree Algorithm. *Journal of Information Systems Engineering and Business Intelligence*, *5*(1), 57-66.

Frazzetto, D., Nielsen, T. D., Pedersen, T. B., &Šikšnys, L. (2019). Prescriptive analytics: a survey of emerging trends and technologies. *The VLDB Journal*, *28*(4), 575-595.

García-Alonso, C. R., Almeda, N., Salinas-Pérez, J. A., Gutiérrez-Colosía, M. R., Uriarte-Uriarte, J. J., & Salvador-Carulla, L. (2019). A decision support system for assessing management interventions in a mental health ecosystem: The case of Bizkaia (Basque Country, Spain). *PloS one*, *14*(2).

Gardner, J. R., Kusner, M. J., Xu, Z. E., Weinberger, K. Q., & Cunningham, J. P. (2014, June). Bayesian Optimization with Inequality Constraints. In ICML (pp. 937-945).

Gharib Shirangi, M., Oruganti, Y., Wilson, T., Furlong, E., Winter, E., Martin, J., & Yancy, R. (2019, April). Prescriptive Analytics for Completion Optimization in Unconventional Resources. In *SPE Western Regional Meeting*. Society of Petroleum Engineers.

Ghoniem, A., Ali, A. I., Al-Salem, M., &Khallouli, W. (2017). Prescriptive analytics for FIFA World Cup lodging capacity planning. *Journal of the Operational Research Society*, *68*(10), 1183-1194.

Ghosh, R., Gupta, A., Chattopadhyay, S., Banerjee, A., & Dasgupta, K. (2016, June). CoCOA: a framework for comparing aggregate client operations in BPO services. In 2016 IEEE International Conference on Services Computing (SCC) (pp. 539-546).

Giurgiu, I., Wiesmann, D., Bogojeska, J., Lanyi, D., Stark, G., Wallace, R. B., ... & Hidalgo, A. A. (2017). On the adoption and impact of predictive analytics for server incident reduction. IBM Journal of Research and Development, 61(1), 9-98.

Giuseppe, D., Gaeta, A., Gaeta, M., Lepore, M., Orciuoli, F., &Troisi, O. (2016). A new DSS based on situation awareness for smart commerce environments. Journal of Ambient Intelligence and Humanized Computing, 7(1), 47-61.

Groenhof, T. K. J., Asselbergs, F. W., Groenwold, R. H., Grobbee, D. E., Visseren, F. L., & Bots, M. L. (2019). The effect of computerized decision support systems on cardiovascular risk factors: a systematic review and meta-analysis. *BMC medical informatics and decision making*, *19*(1), 108.

Gröger, C., Schwarz, H., &Mitschang, B. (2014, May). Prescriptive analytics for recommendation-based business process optimization. *International Conference on Business Information Systems* (pp. 25-37). Springer, Cham.

Guo, Z., Ngai, E., Yang, C., & Liang, X. (2015). An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment. International journal of production economics, 159, 16-28.

Habeeb, R. A. A., Nasaruddin, F., Gani, A., Hashem, I. A. T., Ahmed, E., & Imran, M. (2019). Real-time big data processing for anomaly detection: A Survey. International Journal of Information Management, 45, 289-307.

Hagerty, J. (2017). planning guide for data and Analytics. *Gartner Inc*, 13.

Harikumar, H., Rana, S., Gupta, S., Nguyen, T., Kaimal, R., & Venkatesh, S. (2018a, November). Differentially private prescriptive analytics. In 2018 IEEE International Conference on Data Mining (ICDM) (pp. 995-1000).

Harikumar, H., Rana, S., Gupta, S., Nguyen, T., Kaimal, R., & Venkatesh, S. (2018b). Prescriptive analytics through constrained Bayesian optimization. PACIFIC-ASIA conferencee on knowledge discovery AND DATA mining, 335–347.

Hayashi, Y., Wakabayashi, K., Shimojyo, S., & Kida, Y. (2019, March). Using decision support systems for juries in court: comparing the use of real and CG robots. In *2019* IEEE *14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (pp. 556-557).

Ho, C. P., &Hanasusanto, G. A. (2019). *On data-driven prescriptive analytics with side information: A regularized nadaraya-watson approach*. Technical report, March.

Horner, V., Rautenbach, P., Mbananga, N., Mashamba, T., &Kwinda, H. (2013). An e-health decision support system for improving compliance of health workers to the maternity care protocols in South Africa. Applied clinical informatics, 4(01), 25-36.

Huang, T., Bergman, D., & Gopal, R. (2019). Predictive and Prescriptive Analytics for Location Selection of Add-on Retail Products. Production and Operations Management, 28(7), 1858-1877.

Hupfeld, D., Maccioni, R., Sesemann, R., &Ravazzolo, D. (2016). Fleet asset capacity analysis and revenue management optimization using advanced prescriptive analytics. *Journal of Revenue and Pricing Management*, *15*(6), 516-522.

Iadanza, E., Goretti, F., Sorelli, M., Melillo, P., Pecchia, L., Simonelli, F., &Gherardelli, M. (2020). Automatic Detection of Genetic Diseases in Pediatric Age Using Pupillometry. IEEE Access, 8, 34949-34961.

Ito, S., & Fujimaki, R. (2017, August). Optimization beyond prediction: Prescriptive price optimization. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1833-1841).

Jank, M. H., Dölle, C., & Schuh, G. (2018, November). Product Portfolio Design Using Prescriptive Analytics. In Congress of the German Academic Association for Production Technology (pp. 584-593). Springer, Cham.

Jiang, C., Jensen, D. L., Cao, H., & Kumar, T. (2010, July). Building business intelligence applications having prescriptive and predictive capabilities. In International Conference on Web-Age Information Management (pp. 376-385). Springer, Berlin, Heidelberg.

Kaur, J., & Mann, K. S. (2018). AI based healthcare platform for real time, predictive and prescriptive analytics using reactive programming. In *Journal of Physics: Conference Series* (Vol. 933, No. 1, p. 012010). IOP Publishing.

Kawas, B., Squillante, M. S., Subramanian, D., & Varshney, K. R. (2013, December). Prescriptive analytics for allocating sales teams to opportunities. In 2013 IEEE 13th International Conference on Data Mining Workshops (pp. 211-218).

Khademolqorani, S., &Hamadani, A. Z. (2013). An adjusted decision support system through data mining and multiple criteria decision making. Procedia-Social and Behavioral Sciences, 73, 388-395.

Kilsdonk, E., Peute, L. W., & Jaspers, M. W. (2017). Factors influencing implementation success of guideline-based clinical decision support systems: A systematic review and gaps analysis. International journal of medical informatics, 98, 56-64.

Kopcso, D., &Pachamanova, D. (2017). Case article—Business value in integrating predictive and prescriptive analytics models. *INFORMS Transactions on Education*.

Krumeich, J., Werth, D., & Loos, P. (2016). Prescriptive control of business processes. Business & Information Systems Engineering, 58(4), 261-280.

Kurniawan, R., Kridalaksana, A. H., &Jundillah, M. L. (2019). Decision Support Systems Selection of Soang Superior Brood Using Weighted Product (WP) and Simple Additive Weighting (SAW) Method. In *E3S Web of Conferences* (Vol. 125, p. 23004). EDP Sciences.

Laude, H. (2018). France's Governmental Big Data Analytics: From Predictive to Prescriptive Using R. In Federal Data Science (pp. 81-94). Academic Press.

Lee, M., Cho, M., Gim, J., Jeong, D. H., & Jung, H. (2014, June). Prescriptive analytics system for scholar research performance enhancement. In *International conference on human-computer interaction* (pp. 186-190). Springer, Cham.

Letham, B., Karrer, B., Ottoni, G., &Bakshy, E. (2019). Constrained Bayesian optimization with noisy experiments. Bayesian Analysis, 14(2), 495-519.

Lo, V. S., &Pachamanova, D. A. (2015). From predictive uplift modeling to prescriptive uplift analytics: A practical approach to treatment optimization while accounting for estimation risk. Journal of Marketing Analytics, 3(2), 79-95.

Martensen, H., Diependaele, K., Daniels, S., Van den Berghe, W., Papadimitriou, E., Yannis, G., ... & Talbot, R. (2019). The European road safety decision support system on risks and measures. *Accident Analysis & Prevention*, *125*, 344-351.

Martinez, E. C., Cristaldi, M. D., & Grau, R. J. (2009). Design of dynamic experiments in modeling for optimization of batch processes. Industrial & engineering chemistry research, 48(7), 3453-3465.

Martínez, E. C., Cristaldi, M. D., & Grau, R. J. (2013). Dynamic optimization of bioreactors using probabilistic tendency models and Bayesian active learning. Computers & Chemical Engineering, 49, 37-49.

Melnikov, Y. B., Ryzhkova, N. G., Ivukina, E. S., & Barkov, F. A. (2019). Monitoring of a Strategy Proficiency as a Tool of the Pedagogical Decision Support System.

Moja, L., Passardi, A., Capobussi, M., Banzi, R., Ruggiero, F., Kwag, K., ... &Vespignani, R. (2016). Implementing an evidence-based computerized decision support system linked to electronic health records to improve care for cancer patients: the ONCO-CODES study protocol for a randomized controlled trial. Implementation Science, 11(1), 153.

Musen, M. A., Middleton, B., &Greenes, R. A. (2014). Clinical decision-support systems. In Biomedical informatics (pp. 643-674). Springer, London.

Navarro-Hellín, H., Martínez-del-Rincon, J., Domingo-Miguel, R., Soto-Valles, F., & Torres-Sánchez, R. (2016). A decision support system for managing irrigation in agriculture. Computers and Electronics in Agriculture, 124, 121-131.

Notz, P. M., & Wolf, P. K. (2020). Prescriptive Analytics for a Queuing Model without Abandonment. *Available at SSRN 3516708.*

Notz, P., &Pibernik, R. (2019). Prescriptive Analytics for Flexible Capacity Management. *Available at SSRN 3387866*.

Poornima, S., &Pushpalatha, M. (2016). A journey from big data towards prescriptive analytics. *ARPN J. Eng. Appl. Sci.*, *11*, 11465-11474.

Pospieszny, P. (2017, October). Software estimation: towards prescriptive analytics. In *Proceedings of the 27th International Workshop on Software Measurement and 12th International Conference on Software Process and Product Measurement* (pp. 221-226).

Power, D. J., & Sharda, R. (2007). Model-driven decision support systems: Concepts and research directions. Decision Support Systems, 43(3), 1044-1061.

Ramannavar, M., &Sidnal, N. S. (2018). A proposed contextual model for big data analysis using advanced analytics. In Big Data Analytics (pp. 329-339). Springer, Singapore.

Rashidi, M., Ghodrat, M., Samali, B., Kendall, B., & Zhang, C. (2017). Remedial modelling of steel bridges through application of analytical hierarchy process (AHP). Applied Sciences, 7(2), 168.

Revathy, P., & Mukesh, R. (2018). HadoopSec: Sensitivity-aware Secure Data Placement Strategy for Big Data/Hadoop Platform using Prescriptive Analytics. *GSTF Journal on Computing (JoC)*, *6*(1).

Ruiz-Ortiz, V., García-López, S., Solera, A., & Paredes, J. (2019). Contribution of decision support systems to water management improvement in basins with high evaporation in Mediterranean climates. *Hydrology Research*, *50*(4), 1020-1036.

Sabou, M., Brașoveanu, A. M., &Önder, I. (2015). Linked data for cross-domain decision-making in tourism. In Information and communication technologies in tourism 2015 (pp. 197-210). Springer, Cham.

Savvopoulos, A., Kalogeras, G., Mariotti, A., Bernini, C., Alexakos, C., &Kalogeras, A. (2019, September). Data Analytics supporting decision making in the Tourism Sector. In 2019 IEEE First International Conference on Societal Automation (SA) (pp. 1-6).

Shroff, G., Agarwal, P., Singh, K., Kazmi, A. H., Shah, S., &Sardeshmukh, A. (2014, July). Prescriptive information fusion. In 17th IEEE International Conference on Information Fusion (FUSION) (pp. 1-8).

Šikšnys, L., & Pedersen, T. B. (2018). Prescriptive analytics. *Encyclopedia of Database Systems, 2nd ed. Springer, New York, NY*.

Siu, P. K. Y., Tang, V., Choy, K. L., Lam, H. Y., & Ho, G. T. S. (2019). An Intelligent Clinical Decision Support System for Assessing the Needs of a Long-Term Care Plan. In *Advances in Intelligent and Personalized Clinical Decision Support Systems*. IntechOpen.

Soltanpoor, R., &Sellis, T. (2016, September). Prescriptive analytics for big data. In Australasian Database Conference (pp. 245-256). Springer, Cham.

Song, S. K., Jeong, D. H., Kim, J., Hwang, M., Gim, J., & Jung, H. (2014). Research advising system based on prescriptive analytics. In *Future Information Technology* (pp. 569-574). Springer, Berlin, Heidelberg.

Song, S. K., Kim, D. J., Hwang, M., Kim, J., Jeong, D. H., Lee, S., ... & Sung, W. (2013, December). Prescriptive analytics system for improving research power. In *2013 IEEE 16th International Conference on Computational Science and Engineering* (pp. 1144-1145).

Soriano, L. T., Capucao, J. N. B., &Palaoag, T. D. (2018). Decision Support Model for Managing Academic Workload in State Universities and Colleges. International Journal of Information and Education Technology, 8(7).

Souza, G. C. (2014). Supply chain analytics. *Business Horizons*, *57*(5), 595-605.

Srinivas, S., & Ravindran, A. R. (2018). Optimizing outpatient appointment system using machine learning algorithms and scheduling rules: a prescriptive analytics framework. *Expert Systems with Applications*, *102*, 245-261.

Stein, N., Meller, J., &Flath, C. M. (2018). Big data on the shop-floor: sensor-based decision-support for manual processes. *Journal of Business Economics*, *88*(5), 593-616.

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., &Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. *npj Digital Medicine*, *3*(1), 1-10.

Tang, V., Siu, P. K. Y., Choy, K. L., Lam, H. Y., Ho, G. T. S., Lee, C. K. M., & Tsang, Y. P. (2019). An adaptive clinical decision support system for serving the elderly with chronic diseases in healthcare industry. *Expert Systems*, *36*(2), e12369.

Thammaboosadee, S., &Wongpitak, P. (2018, October). An Integration of Requirement Forecasting and Customer Segmentation Models towards Prescriptive Analytics For Electrical Devices Production. In 2018 International Conference on Information Technology (InCIT) IEEE (pp. 1-5).

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British journal of management, 14(3), 207-222.

Vakhutinsky, A., Mihic, K., & Wu, S. M. (2019). A prescriptive analytics approach to markdown pricing for an e-commerce retailer. *Journal of Pattern Recognition Research, 1,* 1-21.

Varalakshmi, M., Pavani, P., & Ramadevi, G. (2019). Need, Impact and scope of Prescriptive Analytics. International Journal of Engineering and Advanced Technology, 8(3S), 908-912.

Vater, J., Harscheidt, L., & Knoll, A. (2019, March). Smart Manufacturing with Prescriptive Analytics. In *2019 8th International Conference on Industrial Technology and Management (ICITM)*. IEEE. (pp. 224-228).

Venkatachalam, S., Acharya, S., Oba, K., & Nakayama, Y. (2020). Prescriptive Analytics for Swapping Aircraft Assignments at All Nippon Airways. *INFORMS Journal on Applied Analytics*.

Vinnik, S., & Scholl, M. H. (2005, March). UNICAP: Efficient decision support for academic resource and capacity management. In International Conference on e-Government (pp. 235-246). Springer, Berlin, Heidelberg.

Vohra, R., & Das, N. N. (2011). Intelligent decision support systems for admission management in higher education institutes. International Journal of Artificial Intelligence & Applications, 2(4), 63.

von Bischhoffshausen, J. K., Paatsch, M., Reuter, M., Satzger, G., & Fromm, H. (2015, July). An information system for sales team assignments utilizing predictive and prescriptive analytics. In *2015 IEEE 17th Conference on Business Informatics* (Vol. 1, pp. 68-76).

Walsh, S., de Jong, E. E., van Timmeren, J. E., Ibrahim, A., Compter, I., Peerlings, J., ... & van Wijk, Y. (2019). Decision support systems in oncology. *JCO clinical cancer informatics*, *3*, 1-9.

Wang, C. H., Cheng, H. Y., & Deng, Y. T. (2018). Using Bayesian belief network and time-series model to conduct prescriptive and predictive analytics for computer industries. Computers & Industrial Engineering, 115, 486-494.

Wu, P. J., & Yang, C. K. (2017, May). The green fleet optimization model for a low-carbon economy: a prescriptive analytics. In 2017 International Conference on Applied System Innovation (ICASI), IEEE. (pp. 107-110).

Yoo, C. W., Goo, J., Huang, C. D., Nam, K., & Woo, M. (2017). Improving travel decision support satisfaction with smart tourism technologies: A framework of tourist elaboration likelihood and self-efficacy. Technological Forecasting and Social Change, 123, 330-341.